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On the Aggregation and Monetization of Flexible Loads in the Context of EV Fleets

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Abstract: In this paper, we present an approach to the price-optimized charging of electric vehicles (EVs) based on energy flexibility. Fleet operators determine the minimum and the maximum power demand to charge EVs at a specific time and share this information as so-called power corridors (PCs) with an energy aggregator. The energy aggregator collects the predicted PCs from the fleet operators located in the same market area and aggregates the PCs. The energy provider periodically sends energy prices from the market to the energy aggregator, which purchases energy when its price is opportune. The energy aggregator calculates and delivers charge plans for each fleet operator involved and thus can pass along the purchase prices. The incentive design must ensure that fleet operators are better off by disclosing their flexibility data to the aggregator. This study can contribute to a new data-driven energy market communication system by providing insights on how to leverage the energy flexibility that EVs can offer to the energy system.

Keywords: EV; energy; optimization; smart charging; aggregator; flexibility

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1. Introduction

In 2020, the road transport sector was responsible for 11.9% of greenhouse gas emissions worldwide [1]. To combat human-made climate change, a reduction in these emissions is urgently necessary. One possible strategy to reduce these emissions is the electrification of this sector, resulting in a yearly electrical energy demand of several hundred GWh in Europe [2]. Due to the generally high idle times of passenger cars, this total demand can be flexibly shifted. The charging processes can be scheduled when energy from volatile, renewable energy sources is available or when electricity prices are low. However, the question remains of how this can be implemented in practice. The major challenges are the determination of energy flexibility that fleet operators can offer and the optimization of the EV charging process according to the objective. Current research shows that existing policies of many countries prevent innovative approaches for flexibility trading [3]. Smart charging, i.e., advancing charging processes to times when electricity prices are low or renewable energy is available, is a common approach to running managed charging infrastructures. There are publications that examine smart charging on a theoretical [4–6] and practical basis [7]. The authors of [5] predict potential cost savings of 200 EUR/EV/year if smart charging based on variable prices is applied. Approaches to avoid over-coordination and herding effects have been discussed in the literature on price-based EV charging coordination [8]. One such approach, proposed by [9], involves spatial price differentiation to effectively incorporate distribution grid limitations into charging schedules. Another study by [10] emphasizes potential cost savings achieved by smart EV charging and the ability to feed energy back into the power grid (vehicle to grid, V2G). Various research projects have been working on the aggregation of vehicle fleets' energy consumption to charge them in a price-optimized way. The projects BDL and LamA in Germany can be mentioned [11] as examples. V2X Suisse is another example project in Switzerland [12]. Apart from research institutions, various companies are working on the development of commercial solutions for smart charging. Octopus Energy, for example, has implemented smart charging based on variable electricity tariffs for its customers in the UK using its platform Kraken [13]. The company enel X developed a platform-based solution for smart charging [14]. However, the aggregation process used by these companies is not transparent, and the solutions are proprietary. Open systems are not in the focus of related work.

This paper shows how power demand aggregation can be achieved and how it can be implemented independently of proprietary systems. Improving electrical fleet performance requires a clear objective and measurable variables. The concept of flexibility in general is considered domain-specific and thus difficult to define. In the case when systems should adapt to an external environment, like in our case, adapting the EV fleet to the price of energy, they can adapt better if the variables include flexibility in one or more dimensions [15].

Energy flexibility in our paper is considered as the possibility to adapt the power demand over time. Other definitions for energy flexibility are characterized by static approaches, considering the composition of parameters at a given time instant [16]. Approaches toward a dynamic flexibility function to control demand with penalty signals [15] are a common way to influence consumption behavior and propagate the paradigm shift toward a demand control energy system. The critics argue that penalty-based flexibility indexes depend on the interpretation of the energy providers. These improve their objectives with regard to CO_2 emissions or real-time prices without considering the actual amount of energy demanded by the consumers. Our approach presented in this paper is based on a bidirectional communication and data exchange between fleet operators, energy aggregators, and energy providers. Based on the information that the energy provider receives from energy suppliers and the grid operators, like market energy prices and grid peak times, the aggregated energy orders are being optimized. The goal is to better manage the overall energy and power demand of fleet operators by actively reacting to day-ahead and intraday market prices. This is realized by increasing and decreasing the fleet consumption over the day by controlling the individual charging sessions attuned. The availability of data is the key enabler for our approach to improve power-corridor predictions and the basis for a level playing field for exchanging flexible services between EV fleet operators and energy providers. Our research focuses on the utilization of information to improve the charging processes and costs of commercial EV fleet operators. For this purpose, we address the following research questions:

- What is the optimized usage of EVs in different scenarios like company fleets or rental fleets?
- How can our definition of the power corridor help optimize the energy consumption of EV fleets?
- What are the processes and algorithms required to aggregate and monetize flexible loads of EV fleets?
- What data need to be made available and by whom to feed the algorithms?
- What is required so that our results have an impact on the existing energy landscape?

2. Materials and Methods

2.1. Project Setup

A major goal of the project "*TRADE EVs II*" was to define a framework for addressing the above-mentioned questions. The project, with a duration of three years, was initiated by Elektrizitätswerke Schönau (EWS), Forschungsstelle für Energiewirtschaft e.V. (FFE), nextmove, and SAP in 2021. It involved three fleets with more than 400 EVs driven by employees of the project partners. The project built on the experience and results gained in the predecessor project, "*TRADE EVs I*" (TRADE EVs I, funding code: 01MX16002C), in which a charge schedule heuristic was deployed to optimize energy consumption [16] and a charging system prototype based on Open E-Mobility [17] was set up. TRADE EVs II extends the setup with an energy–flexibility aggregation system to establish the demand-side management for EV charging. In the project, we assessed two approaches for capturing EV data: the hardware-based approach used onboard units, and the software-based solution utilized telemetry services. Based on the accessible EV data, the charging system calculates the energy demand within the respective charging period. The data points considered are, for example, the state-of-charge (*SoC*), the battery model, and the charging priority of EVs.

The project was divided into two main work-streams called Concept and Application, as shown in Figure 1. The conceptual work started with the definition of use cases for controlled charging. The focus was thereby set on the use case of spot-market-optimized charging, in which charging processes are influenced by the current electricity spot-market prices. Subsequently, the concept was extended by integrating it with day-ahead markets, which resulted in the design of an aggregation algorithm and the interfaces required to establish a market communication process.

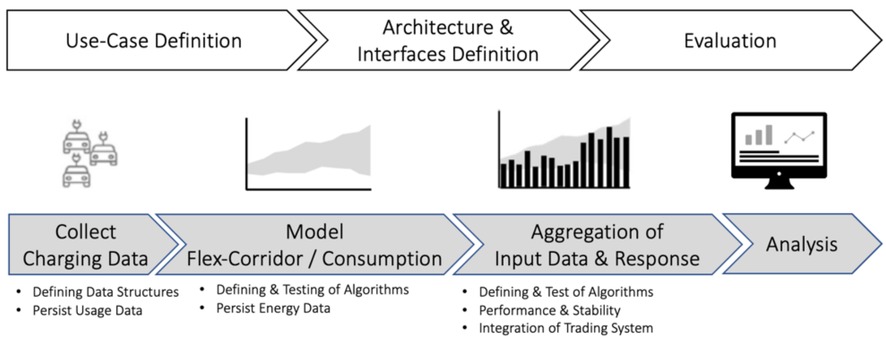

Figure 1. Sequence of project steps.

The application workstream started with the collection of charging data from the participating EVs. We developed a method to determine the flexibility of energy and power consumption of the EV fleets, which we termed "power corridor". In addition, we developed an algorithm to aggregate data about energy demand from different fleets and EV charging sites and to exchange price-related information.

2.2. Definitions and Basics

We assume that only the unidirectional charging of EVs is possible in the system. Hence, the power demand $P \geq 0$ holds at any point in time and energy consumption $E \geq 0$ for any time interval. For the mathematical modeling, we introduce the specific terms "power corridor" *PC*, "energy segment" *ES*, and "energy demand" *ED*. The charging system C can serve n ($n \epsilon \mathbb{N}$) electrical vehicles at the maximum (e.g., limited by the number of installed connectors). Accordingly, at any point of time t, k_t ($0 \leq k_t \leq n \mid k_t \epsilon \mathbb{Z}$) vehicles are supposedly connected. For example, in practice, it could be of interest to know or predict the number of charging EVs at C every 15 min. The connected (i.e., charging) vehicles are denoted as v_i ($i \leq k \mid i \epsilon \mathbb{N}$).

${P_{\min}}^t$ is the minimum power required by C to charge all connected EVs at time t (Equation (1)). Pausing/stopping all charging sessions at time t is equal to $P^t_{\min} = 0$ kW. Note that in practice, unused charging stations, e.g., while in stand-by-mode, could still draw power and consume energy:

$$ {P_{\min}}^t = \sum_{i=1}^{k} {P_{v_i}}^t \mid \min\left(P^t_{v_i}\right). \tag{1} $$

${P_{\max}}^t \geq {P_{\min}}^t$ is the maximum power that can be consumed by C while charging all connected vehicles at time t (Equation (2)). Note that ${P_{\max}}^t$ can basically be limited by the connected EVs' aggregated maximum power demand to charge batteries but also by infrastructure restrictions at C, such as transformer capacity, fuse hierarchies, etc.

$$ {P_{\max}}^t = \sum_{i=1}^{k} {P_{v_i}}^t \mid \max\left(P_{v_i}^t\right). \tag{2} $$

The power corridor PC^t is defined as a set of tuples that contain the maximal consumption power ${P_{\max}}^t$ and the minimum required power ${P_{\min}}^t$ of C at specific points in time (Equation (3)):

$$ PC^t = \left({P_{\min}}^t, {P_{\max}}^t\right). \tag{3} $$

The energy segment ES is defined as the maximum amount of energy, given the maximum and minimum power over time, $P^t_{\max}$ and $P^t_{\min}$, that can be consumed within the time interval t_{s} (start) and t_{e} (end):

$$ ES = \int_{t_{\mathrm{s}}}^{t_{\mathrm{e}}} {P_{\max}}^t - {P_{\min}}^t dt \text{ , } ES \in \mathbb{R}_0^+. \tag{4} $$

The energy demand ED_{v_i} foreseen for vehicle v_i is defined as the difference between the required SoC at departure SoC_{req} and the initial SoC upon arrival SoC_{start} within the time interval from connecting $t_{\mathrm{s}i}$ and disconnecting $t_{\mathrm{e}i}$ the vehicle v_i. Note that the SoC is measured in kWh:

$$ ED_{v_i} = \left(SoC_{\mathrm{req}}^{t_{\mathrm{e}i}} - SoC_{\mathrm{start}}^{t_{\mathrm{s}i}}\right). \tag{5} $$

The total energy demand ED of the charging infrastructure C within the time interval $[t_{\mathrm{s}}, t_{\mathrm{e}}]$ is calculated as the accumulated demands ED_{v_i} of the vehicles v_i that are connected to C:

$$ ED = \sum_{i=1}^{k} ED_{v_i} \mid t_{\mathrm{s}i}, t_{\mathrm{e}i} \in [t_{\mathrm{s}}, t_{\mathrm{e}}]. \tag{6} $$

Figure 2 shows an example power corridor for charging a single EV. The EV is expected to be connected to the charging system between start time t_{s} and end time t_{e}. Within this time range, the required amount of energy for charging can be consumed, depicted as "Energy Demand" (in green). The illustrated power corridor defines boundaries of power that can be drawn by the EV during its stay. As the exemplary corridor has static $P_{\min}$ and $P_{\max}$ values at each point of time, the energy segment (in blue) has the shape of a regular rectangle. This would allow the fleet operator to delay (shift) the start of actual charging, as shown in Figure 2, depending on, e.g., the actual price of energy.

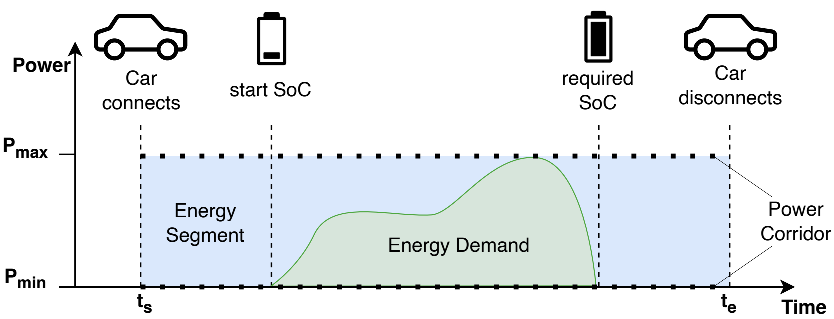

Figure 2. Schematic illustration of a power corridor. The power demand for charging the EV's battery starting by SoC_{start} to the required SoC_{req} level can be set between $P_{\min}$ and $P_{\max}$ within the time interval t_{s} and disconnection t_{e} of the EV.

As shown in Equation (7), the amount of demanded energy ED of C must be between 0 and ES for any time interval of interest. Otherwise, the charging demand cannot be fulfilled.

$$0 \leq ED \leq ES \; for \; [t_s, t_e]. \tag{7}$$

Based on (predicted or otherwise known) ES and ED values in a given scenario and situation, we consider the operator's Flexibility F of shifting demand as

$$F = \begin{cases} \frac{ES-ED}{ES} & \text{if } ES \neq 0 \\ 0 & \text{if } ES = 0 \vee ED = 0. \end{cases} \tag{8}$$

Accordingly, $F = 0$ if $ED = ES$ holds. The flexibility is increasing if

$$0 < ED \wedge ED < ES \longrightarrow F > 0 \; for \; [t_s, t_e]. \tag{9}$$

Table 1 shows two example calculations of two energy demands, $ED1$ and $ED2$, distributed over a seven-hour energy segment ES, accumulated from ES^t for each hour. The power of the charging sessions can be adapted dynamically. In both cases, the energy segment is ES = 104 kWh. In case $F = 0$, the power limit 30 kW of the infrastructure is the restricting factor at $t = 3$ and $t = 4$, so $F = 0$ because $ES < ED$. In the case $F = 0.33$, the energy demand ED_{v_i} of the vehicles v_i is lower, so $ED < ES$ applies.

Table 1. Example illustration of two cases of how flexibility is calculated based on the given PC [$P_{\min}$, $P_{\max}$] in kW, energy segment ES in kWh, two different energy demands $ED1$ and $ED2$ in kWh, and flexibility F. The infrastructure has a power limit of 30 kW.

	Time							***ES***	***ED1***	***ED2***
$\boldsymbol{PC^t}_{v_i}$	**1**	**2**	**3**	**4**	**5**	**6**	**7**		$\boldsymbol{F = 0}$	$\boldsymbol{F = 0.33}$
$PC^t{}_{v_1}$	$[0, 0]$	$[0, 0]$	$[11, 11]$	$[11, 11]$	$[11, 11]$	$[0, 11]$	$[0, 11]$		44	34
$PC^t{}_{v_2}$	$[0, 0]$	$[0, 11]$	$[0, 11]$	$[0, 11]$	$[0, 11]$	$[0, 0]$	$[0, 0]$		30	20
$PC^t{}_{v_3}$	$[0, 11]$	$[0, 11]$	$[0, 11]$	$[0, 11]$	$[0, 0]$	$[0, 0]$	$[0, 0]$		30	16
PC^t	$[0, 11]$	$[0, 22]$	$[11, 30]$	$[11, 30]$	$[11, 22]$	$[0, 11]$	$[0, 11]$			
ES^t	11	22	19	19	11	11	11	104	104	70

Energy segments ES forecasted with long timeframes hence hold a larger flexibility potential than ES with short timeframes and might be of substantial value for energy providers to realize demand-side management. The interface for exchanging this flexibility information is the precondition to create insights into how charging can be improved to save costs by grid-friendly operation.

Equations (7)–(9) are valid under the conditions that $P, ED, ES \geq 0$. By including renewable energy sources and bidirectional charging into the mathematical model, there is also the negative flexibility case imaginable if the energy demand is $ED < 0$:

$$0 > ED \wedge ED > -ES \longrightarrow F > 0 \; for \; [t_s, t_e], \tag{10}$$

$$PC = -ED \vee ED = -ES \longrightarrow F = 0 \; for \; [t_s, t_e]. \tag{11}$$

Other definitions of energy flexibility focus on the responsiveness of consumer behavior to signals like CO_2 intensity or the energy price. For example, they define a dynamic flexibility function to evaluate consumer behavior and how they react to the real-time energy situation. The calculated flexibility index can be used to apply penalties to influence the behavior of the consumers [15]. Our approach, in contrast, focuses on the transparent communication of energy demands and the power consumption the fleet operators are able to adjust for time. This enables the energy provider to allocate and plan the consumption and allows the aggregated fleets to receive the demanded power and energy by adapting consumption plans within their self-defined possibilities.

2.3. Challenges

Besides difficulties in predicting a fleet's energy consumption, the forecasting of local energy supply—especially for renewable energies—comes with challenges as well. This is partly due to analog measuring technology (missing digital data) and weather influences on energy generation. On the other hand, it is also due to static electricity tariffs, which cannot reflect the share of renewables and conceal information about the consumed energy. Providing dynamic tariffs can motivate fleet operators to shift demands and improve the sustainable charging behavior of self-interested charge point operators. In our setup, fleet operators need to specify the extent to which their power demand is defined with the *PC*, and the energy demand *ED* for the EVs. This holds another challenge because rational participants cannot be expected to prioritize the performance of the system over their own interests. Therefore, it is crucial to establish incentives that encourage the revelation and provision of flexibility among the participants. The incentive design must ensure that all are better off by disclosing their flexibility data, which means that they should receive benefits for revealing their information compared to withholding it. This allows the participants to adapt their behavior more flexibly while maximizing their utility. Ultimately, to ensure everyone's participation in the mechanism, it is essential to guarantee individual rationality, as well as the appropriate incentive and coordination mechanisms [15]. Data availability is the basis for improving the forecasting quality of the PC, as seen in the manufacturing industry, wherever even minor process adjustments can generate substantial value [18]. Slight variations in the power system's flexibility can also have a significant impact on economic results. To make the most of this flexibility, it is essential to have a clear understanding of the available flexibility resources.

2.4. Implementation Approach

Addressing the challenges according to flexible energy demand, we evaluate three different controlling scenarios, one for each of the three fleet types, small company fleet, rental car fleet, and large company fleet. All scenarios interact with the central aggregation system. The aggregator system transfers information between consumption facilities, generation facilities, and authorized market partners to generate value via the deliberate placement of energy purchase orders influenced by the different interests of the actors. Figure 3 shows the flow of actions that are conducted on a daily basis. The value is generated by the allocation of the forecasted energy demand within the flexible time range of the three consumers. With the incentive to charge when energy prices are low, the overall energy costs should be lowered.

In the first scenario, a smaller fleet with 15 EVs of the German energy provider EWS is involved. The EVs can use 10 AC charging points located at a company parking space. Each charge point (CP) is managed solely by its charging controller, which only communicates with the charging EV. In this scenario, the total load is set by the consumption of the EVs connected to the charging stations onsite. The forecast of the demanded charging energy at the site is trained based on the consumption data from the EV charging sessions on a daily basis. The prediction functions were continuously applied to increase the overall accuracy of the charging forecasts, for example, if new charging points and EVs are connected. EV drivers are aware that the charging session can be shifted to different timeslots during the parking period to avoid charging during price peaks.

The second scenario is the load-management scenario at nextmove, which has implemented peak shaving to operate more charge points in sequence than would be possible in parallel. The limitation of the connected load and local energy shortages have also been considered. The nextmove dataset has been provided from a rental fleet that contains 320 EVs of different usage types, such as business, private, and test drives. Currently, the fleet consists of 245 midsize battery EVs (35 kWh up to 64 kWh) and 75 large battery EVs (up to 120 kWh). The journeys were planable, and especially the business customers used the cars for frequent traveling. Most drivers use the rental to test an EV before buying it, which includes pushing it to its limits. For example, we observed that at the beginning of the rental period the *SoC* is much lower when the first charging session starts compared to the other charging sessions for the rest of the rental period. Within this scenario, we conducted experiments with push notifications and suggested charging when energy prices were low. In return, the EV drivers received a discount per kWh for their charging session. Wherever possible, in-car data have been used for the charging power prediction of individual cars. In the next step, these data were combined for several locations equipped with nextmove charging sites to calculate the energy demand for day-ahead activities. The rental station charging sites were already operated with a load management system to reflect the local grid's limitations and to adapt to the charging schedule received from the aggregator.

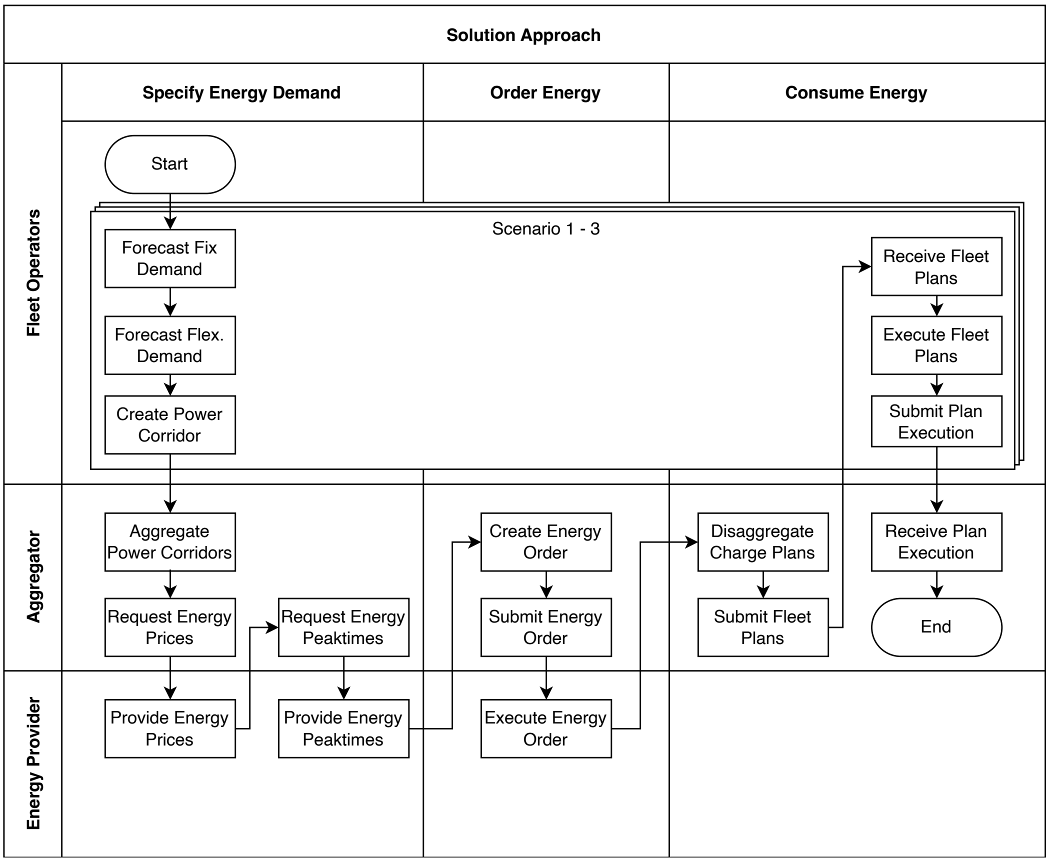

Figure 3. Flow chart of the solution approach per phase and actor of the demonstrator.

The third scenario at SAP is a smart-grid scenario, which integrates information from the local grid to actively steer the total consumption of a charging system with 81 installed charge points [17] serving 400 long-range employee EVs. This scenario integrates information from the local energy management system, which controls onsite photovoltaic (PV) and battery storage. Every 15 min, an optimization of the local consumption is triggered by a heuristic-based optimization model to minimize peak demand, load imbalance, and electricity costs [16]. The functionality to minimize the cost of electricity considers the availability of onsite photovoltaic energy generation as a complementary energy source but does not integrate external energy prices yet. This function requires additional data about fine-grained energy prices from the aggregator, which is planned as a prospective feature. The entire site can offer, by a simple estimation, a flexible energy potential from +20% to −20% of the planned fleet consumption (limited by the maximum allowed load of the site, 680 kW). The total charging capacity of all charge points is 1020 kW. Therefore, the infrastructure is always operated according to the site's maximal load. Additional local PV generation of 80 kWp and a 150 kWh stationary battery offer additional flexibility. Figure 4 shows a single charging plan for an EV, which is created by the optimizer to reduce the peak load in the grid at the SAP site.

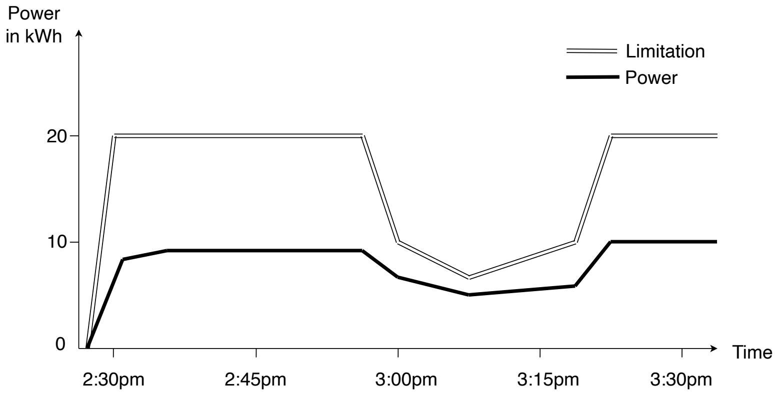

Figure 4. Definition of a CP charging plan based on the charging optimizer of a changing system. The CP charging plan provides the power limitation per charge point for every minute of the charging session. The actual power drawn from the EV for charging the battery is below the limitation.

For the implementation of the charging systems, we use open-source software [17]. All software systems are deployed as containerized applications on web services. The user interfaces are realized as desktop web applications, and there is also a mobile app for EV drivers. Each system runs independently of the other systems with separate persistence and application layers, therefore we are following decentralized architecture principles, which allows more specific conversions into marketable solutions.

2.5. Data Access for Optimization Data

Three different interfaces have been used by the fleet operators during the project to access real-time information from the charging sessions. Figure 5 shows the interfaces implemented for the charging system.

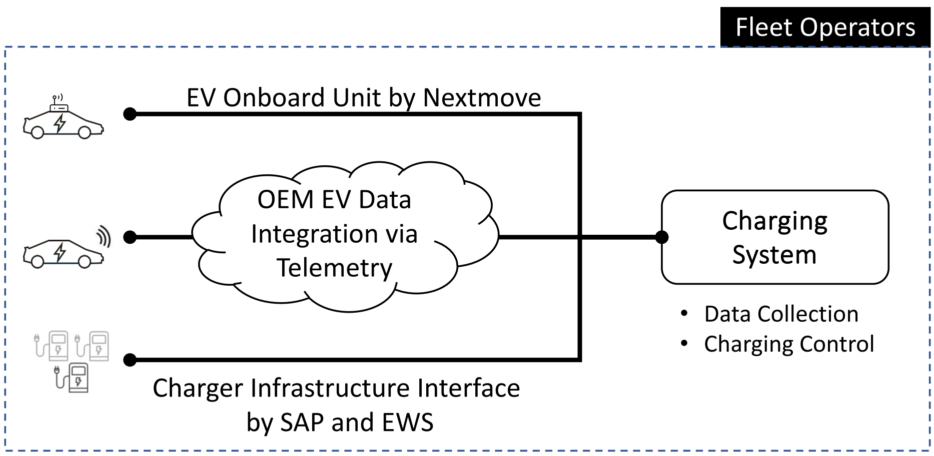

Figure 5. Different interfaces that are evaluated to access real-time charging session information.

2.5.1. Operations Based on Charge Point Data

All three scenarios use the open charge point protocol (OCPP) version 1.6. to exchange charging parameters for authentication and real-time charging session information to deploy charge plans. With data augmentation from an EV database and a user database, heuristical optimization problems like prioritization and the load management of charging sessions are implemented in the charging system [7,16]. The charge point data source is the basic data source for the charging systems in all three scenarios.

2.5.2. Hardware-Based Onboard Units for Real-Time Data

The onboard unit used for the project consists of a transmitter module using onboard diagnostics (OBD) as a data interface. During the project the onboard units support 51 different EV models from nextmove for real-time monitoring. The transmitter was implemented to be capable of obtaining over-the-air updates from the monitoring backend via its mobile connection to access the EV data interface. The price estimate for the developed onboard unit is approximately EUR 450 plus an additional data plan for connectivity. Due to firmware updates in the EV regarding in-car energy management, it was necessary to update during the project 300 units over-the-air. The availability of in-car real-time data depends on the car's state to prevent potential vampire losses during parking periods.

2.5.3. Software-Based Telematic Services for Real-Time Data

The enabling technology for software-based EV data access was realized with a telemetry service providing integration into the cloud services of the EV manufacturer for processing *SoC* information in real time. EV drivers from the SAP site in Mougins/France provided their consent for using the charging data for research purposes. For a yearly fee of EUR 60 per car, the service can be used without any hardware dependencies. Figure 6 shows a charging session with real-time optimization considering the *SoC* is provided by a telemetry service.

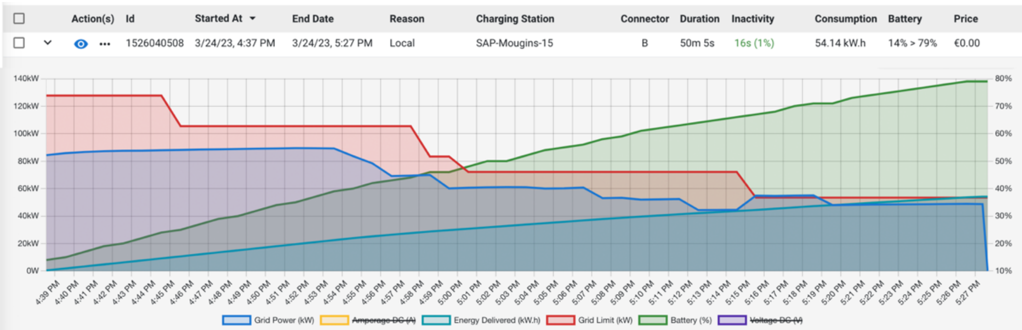

Figure 6. Example of a charging session in the demonstration charging system of SAP [17]. An increasing state of charge lowers the power consumption, and at 80%, the charging session ends.

3. Results

In this chapter, we detail the results of our experimental system setup. First, we outline the system architecture. Afterward, we present the evaluation process and describe the usage of EVs within the project.

3.1. System Architecture

The system mainly serves the needs of three types of entities called "fleet operator", "aggregator", and "energy provider". Each of these has its responsibilities and tasks. The architecture of the demonstrator in Figure 7 shows the entities' connected systems in a cascading pattern. Each fleet operator runs a charging system to control the energy consumption based on the charge plan for the own EV fleet. The aggregator operates an aggregation system that accumulates the demands from the connected fleet operators and communicates the aggregated flexible loads to the energy provider. In the trading system of the energy provider, the respective purchase orders are created and placed in the energy market.

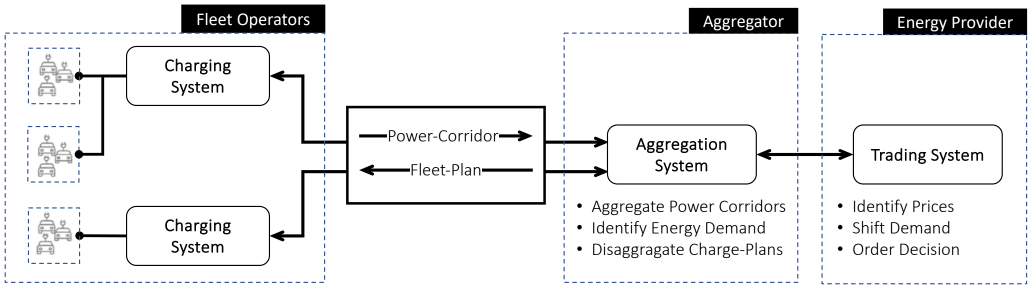

Figure 7. High-level architecture and main information flows between the involved roles within the demonstrator system.

Fleet operators have the task of charging the EVs of the users in an acceptable time while minimizing the cost of charging by considering CO_2 emissions, energy prices, and the local infrastructure situation. For the experimental setup, the fleet operators are obliged to share their flexible energy demand and corresponding power corridors in a given timeframe with the energy aggregator. In exchange, the fleet operator receives an EV charging plan from the energy provider, which is cost-optimized. This incentives the fleet operators to adapt the charging sessions of their fleets. The energy provider has the task of aggregating the power corridors and identifying the energy demand of the affected segments. On the energy provider level, the estimated power corridors received from the connected fleet operators are aggregated. Here, the aggregation includes the summation of power maxima and minima, as well as energy demands over the respective periods of time. Furthermore, the aggregation system generates a consistent view of flexibility originating from fleet operators, including slicing of energy demand segments appropriately (which may potentially overlap in different source fleets) and feasibility checking. A technical interface offers aggregated flexibility potentials to the trading system for corresponding procurement on electricity spot markets. According to the flexible energy demand, the trading system finally identifies current price levels and shifts the demand within the flexible range to make the best procurement decision. The best ordering decision is determined by input parameters, such as the current energy price, the grid capacity, and the situation of the charging systems, which are encoded in the aggregated representation of the received power corridors. The result of a procurement decision is a set of orders to be placed on the market and, in response, a set of transactions (trades) executed. All transactions on the market referring to the energy demand are ultimately composed into a schedule, which includes all the charge plans for the fleet operators. For each time slot (typically 15 min), the charge plans contain the total power to be delivered to the fleet operators. After obtaining the pool schedule from the trading system, the aggregation system disaggregates the pool charge plans according to the individual fleet operators' power corridors and energy demands. Herein, the result is a separate charge plan for each fleet operator, which will be propagated to the charging systems. In the next step, the energy provider will also be able to receive real-time consumption data from the charging systems to react to unforeseen changes in consumption, either by shifting loads between fleet operators or placing short-term order decisions on the intraday energy spot market. This mechanism helps minimize the imbalance (i.e., the mismatch between actual energy consumption and the charge plan backed by trades on the market), which would otherwise result in higher overall energy costs. Figure 8 shows an overview of the aggregation, trading, and disaggregation processes. The diagrams show the fleet charging power on the y-axis and the time on the x-axis. Summing up the flexible fleet demands results in the total energy demand of the aggregator (in green). P_{min} and P_{max} display the limits of power consumption that the fleet operators communicate to the aggregator. Based on the price signal and grid power peak information provided by the energy provider, the aggregator creates the price-optimized energy purchase orders according to the communicated power corridors (light blue). From the accumulated ordered energy, the charge plans for the fleet operators (black lines) are being disaggregated and sent to the fleet operators.

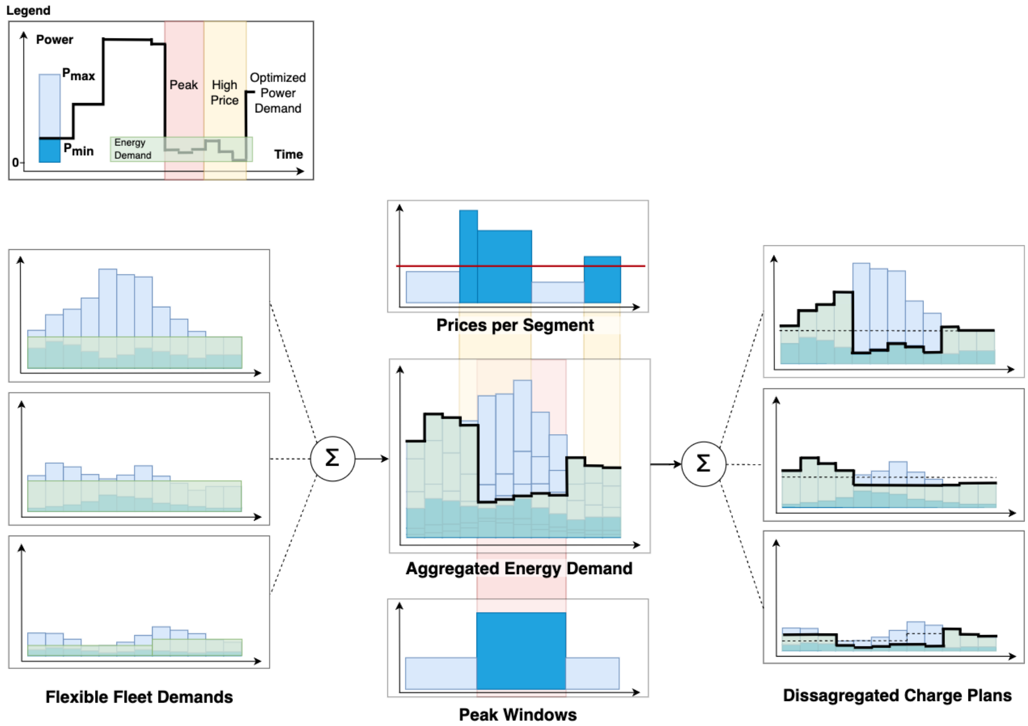

Figure 8. Energy aggregation process. The energy demand is aggregated to place purchasing orders, preferably at times with low prices and no peak loads. The disaggregation considers the minimum and maximum power values communicated by the fleet operators' charging systems.

3.2. Evaluation

The assessment of the implemented system is organized in three steps. The initial step focuses on testing the charging optimization for EVs to align with the local circumstances of the charging systems. The second step involves the collection of data from the charging systems, which will facilitate the forecast and the creation of a power corridor that is realistic to the EV fleet consumption toward the placement of an aggregated energy order in the energy market. In the third step, the breakdown of the centrally ordered energy quantity with real-time allocation processes for flexible demands is outlined. The first evaluation is the optimized usage of EVs in different scenarios depending on the usage of the EVs. In a large-company scenario (SAP), the EVs are regularly available, which leads to similar daily load profiles. For the rental-fleet scenario (next move), the fluctuation of the created monetary value by smart charging depends on the rental behavior and the battery size of the EVs, which are connected to the CPs onsite. For example, groups of transporter EVs are sometimes booked by customers for several weeks and are therefore not available for optimization of the fleet's charge plans. When the EV transporters are returned to the site again, this increases the flexibility of the load profile of the charging system significantly compared to proportionally more passenger EVs charging. Second, our definition of the power corridor allows the purchase of energy for fleet operators in the day-ahead market. Due to the day-ahead charging plan for the fleets, more market transparency can be provided and the aggregator has the possibility to place additional orders on the intraday market. The data created throughout the aggregation processes being evaluated and first simulations show the value of this approach [19]. Third, the algorithms and data required for aggregation and monetization of flexible loads are field-tested. The aggregation algorithm aggregates the data of the fleet consumption forecasts. The algorithm optimizes energy purchasing according to low-cost energy segments and peak windows in the power grid, and the disaggregation algorithm [19] that creates the charge plans for the fleets by calculating the amount of required power to serve the planned fleet demand. Finally, we proposed an overall approach that is already under more specific evaluations by other means and projects from [11–14].

3.3. Discussion

Optimizing the energy consumption of EV charging systems is not a trivial task. The difference between the grid limit and the grid power in Figure 6 shows that EVs do not simply charge up to the power of the assigned charge profile. Instead, each EV has its power plateaus on which it charges. These power plateaus, which are vehicle-model-dependent, are considered in the optimizer of the large-company scenario [7]. However, the power plateaus were not implemented in the rental-fleet and small-company scenarios. The differences in power plateaus allow the classification of EVs into three categories: small (with less than 35 kWh battery capacity), standard (35 kWh up to 64 kWh), and long-range (up to 120 kWh). These categories allow the further analysis of different consumption patterns. Further data analysis shows interdependencies with charge point models, car types, and real-time data to improve the optimization capabilities of the system. To identify the reasons for these different patterns, a survey has been conducted. Based on the test scenarios to forecast the flexible energy demand, customers have been surveyed on how their behavior affects the charging processes. The clustering of the data showed that most EV drivers picked the car to fit their driving scheme. The interview questions were as follows:

- Where is your main location to charge your EV?
- To what extend is your charging behavior affected by energy prices?

The analysis of the results shows that smaller EVs charge up to 80% at home, while standard EVs charge only up to 60% and long-range EV only up to 40% at home. According to these results, long-range EVs are the most relevant EVs for aggregation purposes at charging sites. However, most long-range EV users are not interested in electrical cost optimization at all because they do not need to charge offsite from home. These drivers are often business users and are triggered only by their individual charge demands, which the company pays. They usually use high-performance chargers during travel. The drivers of smaller EVs, on the other hand, are permanently looking for the next charging opportunity. This user group is really interested in the incentives a charging shift would offer them on a daily basis. But the greatest potential is among the standard EV users, which can delay a charging session to the next day. They have a larger battery but still connect often to the grid. Their battery size allows them to dynamically change their charging behavior, if there is a sufficient incentive available. This promises a potential field for development to provide end-user services and products offering optimized energy flexibility.

4. Conclusions

Our approach provides a framework that holds clearly defined areas of optimization for each in our research participating role: "fleet-operator", "aggregator", and "energy provider". Data availability has been identified as the limiting factor during the project to create substantial value from the data. The evaluation is performed based on the data transmitted from three charging systems which cover the presented scenarios: "small company fleet", "rental fleet", and "large company fleet". Data collection was implemented via OCPP, which provided 40,000 charging sessions over the last three years. We could record 8200 charging sessions that were optimized with *SoC* information that was gathered from OBD devices or telemetry services. Even when applying the load profile from the day ahead as an estimation of the power corridor, the purchase decisions of energy could already be improved by the aggregator by considering peak windows and prices, as described in Section 2.4.

The next step is to identify the predictors for charging behavior to improve the prediction accuracy for the power corridors and the flexible energy demand. Potential data sources could be booking systems with travel data, human resource systems with location and business car data, or facility management systems with data about the site infrastructure. Another open problem is to compare the data from the charging system forecasts with the actual energy consumption and the trading data, which can provide insights into how much value can be created with flexible energy consumption and how effective incentive systems can be designed. Viewing it from the business perspective, the consumption of cheaper energy is a promising result because the power corridor as a means for exchanging information between the roles of the fleet operator, aggregator, and energy provider creates transparency that shows improvement potentials of operational processes.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
EV	Electric Vehicle
CP	Charge Point
DC	Direct Current
OBD	On-board diagnostics
OCPP	Open Charge Point Protocol
PV	Photovoltaic
SoC	State of Charge
V2G	Vehicle to Grid

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